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sEMG Wavelet-based Indices predicts Muscle Power Loss during Dynamic Contractions

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sEMG WAVELET-BASED INDICES PREDICTS MUSCLE POWER LOSS DURING DYNAMIC CONTRACTIONS

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ABSTRACT

Purpose: To compare the sensitivity to estimate acute exercise-induced changes on muscle power output during a dynamic fatiguing protocol from new surface electromyography (sEMG) indices based on the discrete wavelet transform, as well as from amplitude and spectral indices of muscle fatigue (i.e. mean average voltage, median frequency and ratios between spectral moments). **Methods**: 15 trained subjects performed 5 sets consisting of 10 leg press, with 2 minutes rest between sets. sEMG was recorded from vastus medialis (VM) muscle. Several surface electromyographic parameters were computed. These were: mean average voltage (MAV), median spectral frequency (Fmed), Dimitrov spectral index of muscle fatigue (FInsm5), as well as other five parameters obtained from the discrete wavelet transform (DWT) as ratios between different scales. **Results**: The new wavelet indices as a single parameter predictor accounted for 46.6% of the performance variance of changes in muscle power and the log FInsm5 and MAV as a two factor combination predictor accounted for 49.8%. On the other hand, they showed the highest robustness in presence of additive white Gaussian noise for different signal to noise ratios (SNRs). **Conclusions**: The sEMG wavelet indices proposed may be a useful tool to map changes in muscle power output during dynamic high-loading fatiguing task.

Key words: Median Frequency, surface EMG, wavelet transform, muscle fatigue.

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sEMG WAVELET-BASED INDICES PREDICTS MUSCLE POWER LOSS DURING DYNAMIC CONTRACTIONS

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Key words: Median Frequency, surface EMG, wavelet transform, muscle fatigue.

INTRODUCTION

Paragraph Number 1 Surface electromyography (sEMG) time parameters (i.e. root mean square amplitude) as well as spectral parameters obtained from the Fourier transform (i.e. spectral parameters as mean and median frequency) have been frequently applied to monitor changes in neural drive during maximal isometric voluntary contractions. During a sustained static contraction, the sEMG amplitude was reported to either increase (3,22,25,28), decrease (34) or remain almost unchanged (26), while mean power spectral frequency usually decreased (3,28,30,38). These controversial data obtained for the amplitude, may be explained by the lengthening of intracellular action potential (IAP) profile in the EMG amplitude characteristics which is a distance dependent effect. It was found using simulations that the EMG amplitude increased with IAP profile lengthening independently of the decrements in IAP amplitude with fatigue. In addition, this increase was greater at larger distances from active motor units, so it seems that this factor may be sometimes more influential on the sEMG amplitude than alterations in neural drive defined by the number of active motor units and their firing rates (2,13).

Paragraph Number 2 Due to its practical implications in daily function, however, the study of sEMG during fatiguing dynamic contractions has recently attracted great attention. During dynamic tasks, several factors such as changes in the number or active motor units, changes in joint angle and fiber lengths as well as changes in force/power though the range of motion, together with the change in muscle fiber conduction velocity due to muscle fatigue may increase the non-stationarity of the myolectrical signal (15,14). Thus, the sEMG amplitude has been observed to increase during submaximal dynamic exercise (37), or decrease during exercises at maximal force (20). In addition, some authors found decrements of mean power frequency (37) while others observed no changes (1,4). It is also likely that the pattern of neural activation is different during dynamic and static contractions so the extraction of information from the sEMG signal during a static contraction to infer fatigue-induced changes during dynamic contractions may be also questionable (11). Vollestad (39) questioned the validity of the amplitude and the spectral shifts of the

EMG signal to assess fatigue observing no straightforward relationship between them. For all these reasons the traditional parameters used to asses change in neural drive during dynamic fatiguing tasks (mean or median frequency) may not reflect accurately changes in the power spectral density (14).

Paragraph Number 3 To overcome the non-stationarity signal condition and the low sensitivity of the traditional parameters during dynamic tasks, new techniques and parameters are needed to monitor muscle fatigue more accurately. In this respect, time-frequency and time-scale processing techniques are more suitable to deal with non-stationary sEMG signals. Bonato et al. (8,7) studied different Cohen class distribution concluding that the Choi-Williams distribution was the more suitable to analyze the sEMG recorded during dynamic contractions. In addition they proposed the instantaneous mean frequency (IMNF) (8) calculated over this distribution, as an index to monitor muscle fatigue during dynamic contractions. However, Karlsson et al. (19) after comparing different time-frequency distributions as the short-time Fourier Transform, the Wigner-Ville distribution, the Choi-Williams distribution and the continuous wavelet transform, concluded that the continuous wavelet transform had better accuracy and estimation capacity than the other time-frequency distributions on simulated data test and consequently better accuracy to map changes in sEMG during dynamic contractions. Using time-frequency and time-scale techniques (i.e. Choi-Williams distribution and wavelet distribution), it was found a shift towards lower frequencies (8) and therefore, a decrease in the IMNF over the fatiguing dynamic contractions (8,27). During dynamic trunk extensions, Sparto et al. (33) used different scales from a Daubechies wavelet function of order 6 to report changes in the power spectrum. They reported positive relationships between maximal torque output and coefficients of the scale 4 (frequency range: 209-349Hz) but negative relationships with the coefficients of the scales number 8 (105-175Hz), 16 (52-87Hz), 32 (26-44Hz), 64 (13-22Hz) and 128 (7-11Hz). In this study, it was suggested that a decrease in high-frequency wavelet coefficients and an increase in low-frequency wavelet coefficients may be related with fatigue during dynamic tasks. Based on the indices of peripheral muscle fatigue Dimitrov et al (12) calculated ratios between EMG power spectral density content

in high and low frequency bands (5,10,29,21). It was suggested that ratios between different spectral moments calculated over the power spectral density obtained using the discrete Fourier transform achieved higher sensitivity under both isometric and dynamic contractions. More precisely, they suggested the use of ratios of moment of order (-1) and moments of order 2 and higher. The reason of the selection of these moment orders was that the spectral moment of order (-1) emphasizes the increase in low and ultralow frequencies in EMG spectrum due to increased negative afterpotentials during fatigue. On the other hand, the spectral moments of order 2 and higher, emphasizes the effect of decreases in the high frequencies due to increments in the duration of the intracellular action potentials and decrements in the action potential propagation velocity. Recently, Gonzalez-Izal et al (17) also showed that the logarithm of the spectral index proposed by Dimitrov (FI_{nsm5}) (calculated as a ratio between spectral moment of order (-1) and spectral moment of order 5) could be useful for monitoring muscle power fatigue after multiple sets of dynamic fatiguing high-power contractions, accounting for 37% of the performance variance of changes in muscle power output. However, the percentage of performance explained by this parameter is not enough to map accurately changes in muscle power output during dynamic contractions. In addition, all these parameters used to assess changes in muscle power output were calculated over the entire power spectrum. Thus, they are normally affected by noise (i.e. noise from the main power supply, noise form the electronic devices, etc.).

Paragraph Number 4 The purpose of this study was to combine the use of wavelet transforms and the ratios between different spectral moments to obtained indices which can explain muscle power output during dynamic contractions. We hypothesized that the five new indices proposed, calculated as ratios of spectral moments and other features between two different wavelet scales, reflecting low and high frequency components of the signals, would be able to predict more accurately changes in muscle power output during dynamic contractions than the other parameters studied. Moreover, the new indices proposed would also show a superior performance when the signal is affected by noise of different levels.

METHODS

A. Experimental design

Paragraph Number 5 Fifteen physically active men (age, 34.2 ± 5.2 yr; height, 177.3 ± 5.6 cm; body mass, 73.1 ± 6.4 kg) (mean ± SD) volunteered to participate in the study. The subjects had experience with recreational training, although no-one of them had been involved in any regular strength training program at the beginning of the study. Each subject gave his written informed consent to participate in the study after being informed about the experimental procedure, its risks and purpose. The experimental procedures were approved by the Institutional Review Committee of the Instituto Navarro del Deporte according to the Declaration of Helsinki. Before inclusion in the study, all subjects were medically screened by a physician and were free from any orthopaedic, electrocardiographic, endocrine or medical problems that would contraindicate their participation or influence the results of the study.

Paragraph Number 6 The protocol was the same to that used in a previous study (17) and consisted of 5 sets of 10 repetition maximum leg press (10RM) (i.e. the heaviest load that could be correctly pressed only 10 consecutive times using the correct technique) with 120 s of rest between sets. Each trial (i.e. leg press action in a sitting position) was performed on a bilateral leg extension exercise machine (Technogym, Gambettola, Italy). The trial began with a knee angle of 90º and a hip angle of 45º, and finalized when subjects extended their legs to achieve a knee angle of 180º and a hip angle of 90º. Muscle power output of the leg extensor muscles was measured during the concentric phase of leg press.

B. Surface Electromyography (sEMG)

Paragraph Number 7 sEMG activity during the extension actions of the leg muscles was recorded from the vastus medialis (VM) of the right leg by pairs of bipolar surface electrodes (Blue Sensor N-00-S,

Medicotest) with a distance between the electrode's centres of 22mm. After careful preparation of the skin (shaving, abrasion, and cleaning with alcohol), electrode pairs were placed longitudinally on the middle portion of the muscle.

Paragraph Number 8 EMG signals were recorded at a sampling rate of 1kHz with a Muscle Tester ME3000 (Mega Electronics Ltd) (bandwidth of 8-500Hz / 3dB and a common mode rejection ratio > 100dB). To facilitate and normalize the analysis, the knee movement was divided into 4 intervals of 22.5º. The parameters analyzed in the present study corresponded to the first interval of the movement of the dynamic contractions (from 90º to 112.5º of knee movement), where the VM had its maximal activation.

C. sEMG-based parameters

Paragraph Number 9 Data analysis was performed off-line using the MATLAB 2008b software environment (The MathWorks Inc., Natick, Massachusetts, USA). Eight parameters were computed from the sEMG signals of each concentric phase of leg press: the mean average voltage, the median frequency, the spectral parameter proposed by Dimitrov (12) and other five new indices proposed by the authors based on the discrete wavelet transform (DWT).

C.1. Mean Average Voltage (MAV)

Paragraph Number 10 MAV was calculated after a full-wave rectification and filtered by a moving root-mean-squared filter with a time constant of 50ms (5), as the integrated EMG divided by the integration time.

C.2. Median frequency (F_{med})

Paragraph Number 11 F_{med} was calculated numerically from the following equation:

$$\int_{f_1}^{F_{med}} PS(f)\cdot df = \int_{F_{med}}^{f_2} PS(f)\cdot df \qquad [1]$$

where *PS(f)* is the EMG signal power spectrum calculated using Fourier Transform, $f_1=8\ Hz$ and $f_2=500\ Hz$ (determined for the bandwidth of the electromyograph).

C.3. The spectral parameter proposed by Dimitrov (F_{Insm5}) (12)

Paragraph Number 12 This parameter was designed to overcome the low sensitivity of the median frequency [1]:

$$FI_{nsm5} = \frac{\int_{f_1}^{f_2} f^{-1} PS(f) \cdot df}{\int_{f_1}^{f_2} f^{5} PS(f) \cdot df} \qquad [2]$$

where *PS(f)* is the EMG power spectrum calculated using Fourier Transform and f_1*=8 Hz* and f_2*=500 Hz*.

C.4. Proposed wavelet indices.

Paragraph Number 13 The discrete wavelet transform (DWT) is a technique that simultaneously obtains a time and a scale representation of signals. Its implementation can be performed by repeatedly filtering the signal with a pair of filters. Specifically, the DWT decomposes a signal into an approximation signal using a low-pass filter h[*n*] and a detail signal using a high-pass filter *g*[*n*]. Both low-pass and high-pass filters are synthesized from the wavelet function $\psi(t)$ and from the scaling function $\varphi(t)$, respectively. The approximation signal is subsequently divided into new approximation and detail signals. This process is carried out iteratively producing a set of approximation signals at different detail levels (scales) and a final gross approximation of the signal. The detail D_j and the approximation A_j at level *j* can be obtained by filtering the signal with *h* and *g*, respectively:

$$D_j[n] = \mathbf{H}\langle A_{j-1}[n]\rangle = \sum_{k=0}^{L-1} g[k] A_{j-1}[2n-k] \qquad [5]$$

$$A_j[n] = \mathbf{G}\langle A_{j-1}[n]\rangle = \sum_{k=0}^{L-1} h[k] A_{j-1}[2n-k] \qquad [6]$$

where $A_0[n]$, *n* = 0,1,…*N-1* is the original EMG sequence and **H** and **G** represent the convolution/down sampling operators. A different formulation of the DWT based on a filter bank can also be found. (35).

Paragraph Number 14 The DWT was calculated using Mallat's algorithm (23). We used the interpolated versions of the detail and approximation signals, without downsampling so that we ended up with the same number of time samples in every one of the calculated signals (detail and approximation signals). We tried

different wavelet functions $\psi(t)$ to calculate the wavelet indices and finally we chose the Symlet 5 (sym5) and the Daubechies 5 (db5), which experimentally yielded the best results.

<u>*Paragraph Number 15*</u> Figure 1 shows the frequency bands related to some detail signals from the DWT calculated using sym5. It can be appreciated that they correspond to a filter bank with constant Q. Besides, Table 1 shows the maximum frequency (F_{max}) (frequency of the peak amplitude of the spectrum) and the range of frequencies corresponding to these wavelet scales. As an example, Figure 2 illustrates the discrete Fourier transforms of the first five detail signals (using the wavelet symlet 5) of a 500 ms EMG.

<u>*Paragraph Number 16*</u> Several indices based on the DWT were designed under experimentation on the sEMG signals. The five more successful indices are presented in this work:

C.4.1. Wavelet indices ratios between moments at different scales.

<u>*Paragraph Number 17*</u> Four parameters were calculated from spectral moments:

(a) *Wavelet ratio between moment -1 at scale 5 and moment 5 at scale 1 (WIRM1551).*

<u>*Paragraph Number 18*</u> This parameter was calculated as:

$$WIRM1551 = \frac{\int_{f_1}^{f_2} f^{-1} D_5(f) \cdot df}{\int_{f_1}^{f_2} f^{5} D_1(f) \cdot df} \qquad [9]$$

where $D_5(f)$ and $D_1(f)$ are the power spectra of the fifth and first scales, respectively of the DWT using the sym5 wavelet, and $f_1=8\ Hz$ and $f_2=500\ Hz$.

(b) *Wavelet ratio between moment -1 at maximum energy scale and moment 5 at scale 1 (WIRM1M51).*

$$WIRM1M51 = \frac{\int_{f_1}^{f_2} f^{-1} D_{\max}(f) \cdot df}{\int_{f_1}^{f_2} f^{5} D_1(f) \cdot df} \qquad [10]$$

Paragraph Number 19 where $D_{max}(f)$ and $D_1(f)$ are the power spectra of the maximum energy scale and the first scale, respectively of the DWT using the db5 wavelet, and $f_1=8\ Hz$ and $f_2=500\ Hz$. The maximum energy scale in this work was usually scale 4.

(c) *Wavelet ratio between moment -1 at scale 5 and moment 2 at scale 2 (WIRM1522).*

$$WIRM1522 = \frac{\int_{f_1}^{f_2} f^{-1} D_5(f) \cdot df}{\int_{f_1}^{f_2} f^{2} D_2(f) \cdot df} \qquad [11]$$

Paragraph Number 20 where $D_5(f)$ and $D_2(f)$ are the power spectra of the fifth and second scales respectively of the DWT using the db5 wavelet, and $f_1=8\ Hz$ and $f_2=500\ Hz$.

(d) *Wavelet ratio of energies at scales 5 and 1 (WIRE51):*

$$WIRE51 = \frac{\sum_{i=1}^{N} D_5^2[n]}{\sum_{i=1}^{N} D_1^2[n]} \qquad [12]$$

Paragraph Number 21 where $D_5[n]$ and $D_1[n]$ are the detail signals at scales five and one respectively of the DWT calculated using the sym5 wavelet.

C.4.2. Wavelet ratio between square waveform lengths at different scales (WIRW51).

Paragraph Number 22 The waveform length is a parameter that measures the cumulative changes in amplitude from time sample to time sample over the whole signal. The waveform length effectively encapsulates the amplitude, frequency, and duration of the EMG signal in one simple formula (40). The index was calculated as:

$$WIRW51 = \frac{\sum_{i=2}^{N} \left| D_5[i] - D_5[i-1] \right|^2}{\sum_{i=2}^{N} \left| D_1[i] - D_1[i-1] \right|^2} \qquad [13]$$

where $D_5[n]$ and $D_1[n]$ are the details at scales five and one respectively of the DWT calculated using the sym5 wavelet.

D. Behavior of the sEMG parameters with different levels of noise.

Paragraph Number 23 By adding zero-mean white Gaussian noise to the sEMG signals recorded during the dynamic contractions, a series of sets of noisy sEMG signals with different SNRs were constructed.

E. Statistical analysis

Paragraph Number 24 All the statistical analysis were performed using SPSS 17.0 software. Results were given as mean and error standard values. Changes in percentage between each variable (i.e. sEMG-based parameters and muscle power output) and the average of the values of the first two contractions were calculated. In the cases where the percentage changes did not follow a normal distribution, the corresponding variables were log-transformed. One-way analysis of variance (ANOVA) was used to calculate the significant differences in the average of the values of the parameters recorded in 5 consecutive contractions. Pearson product–movement correlation coefficients (R) were used to determine the association between changes in muscle power output and sEMG-based parameters. A stepwise multiple linear regression analysis was used to relate power output changes with the set of all sEMG-based parameters. The independent variables (e.g. changes in log FInsm5, spectral median frequency, amplitude and changes in log WIRM1551, WIRM1M51, WIRM1522, WIRE51 and WIRW51) entered into the stepwise procedure.

Paragraph Number 25 To compare the goodness-of-fit of the simple regressions of the sEMG parameters, the residual values of their regressions were used (the lower the variance of the residuals, the higher the accuracy of the simple regression models). Levene's test was applied to test the equality of the variances of the residual values of the regressions.

Paragraph Number 26 Secondly, the normality of the square residuals was analyzed. A Box-Cox transformation, taking the power 0.25 of all square residuals, was applied to get the normality for data.

Then, a one way ANOVA was applied to these transformed residuals to test the equality of their means (as an alternative way to test the equality of the variance of the residuals). After rejecting the null hypothesis a post-hoc analysis to build homogeneous groups was performed by using the Duncan method. Equivalent subgroups of regression models were obtained.

Paragraph Number 27 Pearson product–movement correlation coefficients (R) were used to determine the association between all the sEMG-based parameters obtained from the sEMG signals with different levels of noise and muscle power output were calculated and plotted against SNRs values. The $P \leq 0.05$ criterion was used to establish statistical significance.

RESULTS

A. Exercise-induced muscle power changes

Paragraph Number 28 Figure 3 illustrates the average muscle power output of the first and last contractions and the evolution of the muscle power output percentage changes along the 50 leg extensions. Muscle power output of the last repetitions of each set was significantly lower ($P \leq 0.05$) than that recorded during the corresponding first two repetitions. The muscle power output of the last repetition of the fifth set was 45% lower ($P \leq 0.05$) than that recorded during the initial first two repetitions of the first set.

B. Changes in sEMG indices over time

Paragraph Number 29 Figure 4 shows the percentage changes of different sEMG-based parameters along the 50 leg extension. The values of the logarithm of the new wavelet indices (Fig 4d, 4e, 4f, 4g, 4h) and the logarithm of FI_{nsm5} (Fig 4c) significantly increased ($P \leq 0.05$) during the last five repetitions of each set and the first ones of the 3rd, 4th and 5th set compared to the values of the first five repetitions of the 1st set. The MAV values of the last 5 repetitions of each set were significantly ($P \leq 0.05$) higher (Fig 4a), whereas the Fmed values were significantly ($P \leq 0.05$) lower than those recorded during the first five repetitions of the 1st set (Fig 4b).

Paragraph Number 30 Comparing the range of variability among parameters, it was found that FI_{nsm5} presented higher range of variation than Fmed. The maximal changes of FI_{nsm5} observed was approximately five fold (before calculating the logarithm), whereas that of Fmed was only 22%. Moreover, the wavelet indices had even more range of variation (between seven to fifteen fold) than $FI_{nsm5,}$ therefore they presented the highest ranges of variation in all cases.

C. Relationships between sEMG-based parameters and Muscle Power Output changes

Paragraph Number 31 Pearson correlation analysis revealed that the new wavelet indices showed greater correlations values with muscle power output [log-WIRM1551 (R= -0.635; P<0.05); log-WIRM1M51 (R= -0.576; P<0.05); log-WIRW51 (R= -0.683; P<0.01); log-WIRE51 (R= -0.674; P<0.05) and log-WIRM1522 (R= -0.650; P<0.05)] than those reported with other sEMG indices [MAV (R= -0.506; P<0.05), log-FI_{nsm5} (R= -0.518; P<0.05) and Fmed (R=0.435; P<0.05)] (Table 2). In Figure 5 they are shown the regressions of Fmed, log-FInsm5 and the logarithm of the two wavelet indices which presented higher correlation coefficients (log-WIRW51 and log-WIRE51).

Paragraph Number 32 Stepwise multiple linear regression analysis with muscle power changes as a dependent variable and the individual values of the different sEMG parameters obtained during the fatiguing dynamic protocol as independent variables showed that the log-WIRW51 as a single parameter predictor accounted for 46.6% of the performance variance of changes in muscle power, and the log-WIRW51 and MAV, as a two factor combination predictor, accounted for 49.8% of the performance variance of changes in muscle power, respectively.

D. Goodness-of-fit of the regressions

Paragraph Number 33 The result of the Levene's test was significant (P<0.001) over the residuals of all simple regression models, so these simple regressions between muscle power output and sEMG-based parameters were not assumed equal. Fig. 6 illustrates the confidence intervals of the standard deviations of the residuals for each simple regression model. It can be appreciated that the variability of the residuals of

the wavelet indices was similar to each other but lower than the residuals of the other sEMG-based parameters (Fmed, FInsm5 and MAV).

Paragraph Number 34 The power transformation of the squared residuals with a power of 0.25 (Box-Cox transformation) provides a normal distribution for these transformed residuals (obtained as the square root of the absolute residuals values, in short SRARs). In agreement with the Levene's test result, the ANOVA test applied to the SRARs rejects the null hypothesis of equal variances for the residuals, meaning that the simple regressions between muscle power output and sEMG-based parameters were not assumed equal.

Paragraph Number 35 Fig. 7 shows the mean of SRARs for each sEMG parameter and the four different homogeneous subgroups formed by Duncan's test ($P \leq 0.05$). The subgroups were formed by the parameters whose regressions could be considered equivalents. Observe that the first subgroup contained only the wavelet indices and the fourth subgroup contained the rest of indices (MAV, Fmed and log-FI_{nsm5}). Since the mean value of the first subgroup was significantly smaller than those of the rest of subgroups, then it could be affirmed that the wavelet indices are the parameters that best fitted the changes in muscle power output. We also obtained two intermediate homogeneous groups composed by indices of both types.

E. Comparison among sEMG-based parameters to monitor muscle power output with different levels of noise

Paragraph Number 36 Fig. 8 illustrates how the Pearson correlation coefficients of the relative changes of all the indices used to estimate power output varies with SNR of the sEMG signal (i.e., with the noise level). As expected the magnitude of the correlation coefficient decreased with the noise level (i.e., increased with the SNR). It can also be appreciated that wavelet indices were more robust against noise than the other parameter examined. The log-WIRM1522 achieved the highest correlation coefficient from 2 to 20db. No changes in the performance of the wavelet parameters were found for levels of SNR of 30dB and 40dB, and log-WIRW51 and log-WIRE51 were the parameters with higher Pearson correlation coefficients with muscle power output.

DISCUSSION

Paragraph Number 37 The main results obtained in this study showed that the new indices obtained from the discrete wavelet transform (DWT) as ratios between different scales, provided greater accuracy to map losses in muscle power output than the other sEMG-based parameters studied. These results suggested that the new proposed indices could be useful to map more accurately changes in muscle power output during multiple sets of dynamic high-power contractions.

Paragraph Number 38 The amplitude increments during the fatiguing protocol found in this study, were in agreement with the results obtained by some researchers from fatiguing dynamic knee extensions protocols (24,31,37), during cycling (9) and during elbow flexions and extensions (32). However, other authors found decrements in amplitude during fatiguing knee extension protocols (16,20). As suggested by Arabadzhiev et al (2) using computer simulations, these controversial results could be related with the lengthening of intracellular action potential (IAP) typical for fatiguing contractions. This factor could have a stronger effect on EMG amplitude characteristics than alterations in neural drive defined by the number of active motor units and their firing rates. In addition, Dimitrova and Dimitrov (13) suggested that the amplitude of motor unit potentials (MUP) and M-waves depends on the electrode position and it could change with fatigue in different ways according to the electrode position with respect to the active fibers. They suggested that the amplitude of MUPs and M-waves could decrease with fatigue close to the active fibers, be almost unchanged at middle distances and increase far from the fibers even though the IAP amplitude was supposed to decrease. Therefore, these distance-dependent effects of the MUP amplitude could explain the different results obtained by different researchers.

Paragraph Number 39 In agreement with previous fatiguing dynamic knee extension protocols (12), exercise-induced decreases in mean power output was related in the present study to significant increases of spectral indices calculated as ratios between moments of different order (e.g. the new wavelet-based indices

and the index proposed by Dimitrov et al.). In addition, exercise-induced decrease in power output was related with a decrease in the median frequency during knee extension protocols (16,18,24,37) or cycling (9), reflecting a shift of EMG power spectrum to lower frequencies. However, these results were in contrast with other studies that showed no changes in the mean power frequency during walking until fatigue at 5km/h and at 25% (4) and 20% (1) or during knee extension protocols in subjects with a high percentage of slow twitch fibers (20). According to Bigland-Ritchie et al. (6) these changes in the frequency spectrum towards low frequencies, may be partly related to an increase in the duration of the motor unit action potential waveform and a subsequent decrease in muscle fiber conduction velocities.

Paragraph Number 40 A unique finding of the present study was that the new DWT-based parameter (log-WIRW51) could be useful for monitoring muscle power fatigue after multiple sets of dynamic fatiguing high-power contractions, accounting for 46% and 49% in combination with MAV of the performance variance of changes in muscle power output. In addition, the relationship between the muscle power output changes, the new DWT-based parameter and the index proposed by Dimitrov were higher than that reported with the other sEMG based parameter (i.e. amplitude and median frequency). Dimitrov et al (12) found similar results in a study during a dynamic protocol consisting of 10 bouts of 15 right knee-extensions, lifting 50% of their one repetition maximum. The concluded that the application of their spectral index provided a better monitoring of peripheral muscle fatigue in comparison with the traditional median frequency. All these results are in agreement with the results obtained by Gonzalez-Izal et al. (17) reporting that the logarithm of the spectral parameter proposed by Dimitrov (12) was the sEMG-based parameter which most accurately monitored changes in muscle power output (e.g. accounting for 37% of the performance variance of changes in muscle power output) during the same protocol to the one performed in this study. Furthermore, in the present study it was found that the Pearson correlation values were greater for the new DWT-based parameters than for the Dimitrov's spectral parameter. Therefore we

claim that the new parameters are useful tools to map changes in muscle power output during dynamic contractions.

Paragraph Number 41 On the other hand, as suggested by Dimitrov and coworkers (12) the higher ranges of variability confer greater sensitivity to a specific parameter to explain muscle fatigue. Thus, in the present study the highest ranges of variability related to the actual power changes achieved by the new wavelet indices suggest that these parameters are the most sensitive parameters to measure peripheral muscle fatigue during dynamic contractions. It is also likely that the higher the range of variability of the new fatigue index makes it more suitable to explain the changes in the sEMG signals related to peripheral muscle fatigue. In addition they are shown higher Pearson product–movement correlation coefficients by using multiple regression techniques. Moreover, the better results of the new wavelet indices may indicate that certain frequency bands change most consistently with muscle fatigue.

Paragraph Number 42 To measure the robustness of the parameters against noise, Gaussian noise was added to the sEMG signal. This procedure was used for some researchers as Stulen and DeLuca (36) to measure the percentage error in the mean and median frequency of the myoelectric signal after adding different levels of white noise. It was showed that the median frequency was less affected by noise, particularly if the noise was present in the high-frequency band of the EMG spectrum. In the present study, after Gaussian noise addition to the sEMG signals higher correlation coefficients were observed with changes in muscle power output. It is suggested that the new spectral DWT-based parameters are more robust against noise than the other parameters. In addition, since white additive Gaussian noise disturbs the complete power spectrum of the sEMG signals, parameters such as the log-FI_{nsm5} and median frequency calculated over the entire power spectrum were more affected by noise. In contrast, the robustness against noise achieved by the wavelet indices can be related to a lesser noise presented in their narrower frequency bands. In addition, the differences in robustness against noise between log-WIRM1522 and the other wavelet indices could be related to the fact that this parameter makes use of wavelet scale 2 (instead of

wavelet scale 1 as the other wavelet indices). In doing so, this parameter is less disturbed by noise since it uses the scale 2, which has a narrower bandwidth than wavelet scale 1.

Paragraph Number 43 It is important to note that these results reflect the robustness and the performance of the wavelet indices in the presence of Gaussian noise only. Further studies are required to investigate the behavior of these new wavelet indices under different conditions and muscles and also in presence of other kind of noise sources different from Gaussian noise. One of these sources presented in almost all kind of experimental recordings is the noise produced by the main power supply, with frequency ranges 45-55 Hz in Europe or 55-65 Hz in USA. However, this kind of noise will hardly affect the results of most of the wavelet indices achieved in this work. This is due to the fact that the frequency bands for the wavelet scales 1 and 5 have zero or a very low gain response to these frequency ranges (45-65Hz), as it is shown in Fig. 1. However, other specific sources of noise should be taken into account depending on the kind of exercise movement. Nevertheless, this analysis provided a starting point with promising results in the development of indices which are able to map changes in muscle power output less affected by noise.

Paragraph Number 44 In conclusion, the sEMG DWT-based indices proposed in this work are more adequate to assess changes in muscle output than previous approaches, even in the presence of additive Gaussian noise in the sEMG signal.

ACKNOWLEDGMENTS

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TABLES

	D_1	D_2	D_3	D_4	D_5
F_{max} (Hz)	492	171.75	85.75	44.5	22.25
Frequency range (Hz)	249.75-500	122.5-255.5	61.25-127.5	31.25-62.75	15.75-31.25

Table 1. Maximum frequency (F_{max}) (frequency of the spectral peak amplitude) and frequency ranges for the first five DWT scales using sym5. Frequency ranges include frequencies with amplitude spectrum greater than 0.707 of the amplitude spectrum of F_{max}.

	MAV	Fmed	Log-FInsm5	Log-WIRM1551	Log-WIRM1M51	Log-WIRW51	Log-WIRE51	Log-WIRM1522	Muscle Power Output
MAV		-0.486**	0.576**	0.474**	0.680**	0.515**	0.502**	0.467**	-0.506**
Fmed			-0.537**	-0.517**	-0.602**	-0.564**	-0.560**	-0.579**	0.435**
Log-FInsm5				0.787**	0.884**	0.727**	0.742**	0.638**	-0.518**
Log-WIRM1551					0.765**	0.945**	0.964**	0.917**	-0.635**
Log-WIRM1M51						0.719**	0.719**	0.610**	-0.576**
Log-WIRW51							0.994**	0.955**	-0.683**
Log- WIRE51								0.961**	-0.674**
Log-WIRM1522									-0.650**
Peak Power									

* Significant correlation coefficients P<0.05
** Significant correlation coefficients P<0.01

Table 2. Correlation coefficients between changes (%) in the sEMG parameters and the corresponding changes (%) in muscle power output. (** P<0.01; * P<0.05)

FIGURES

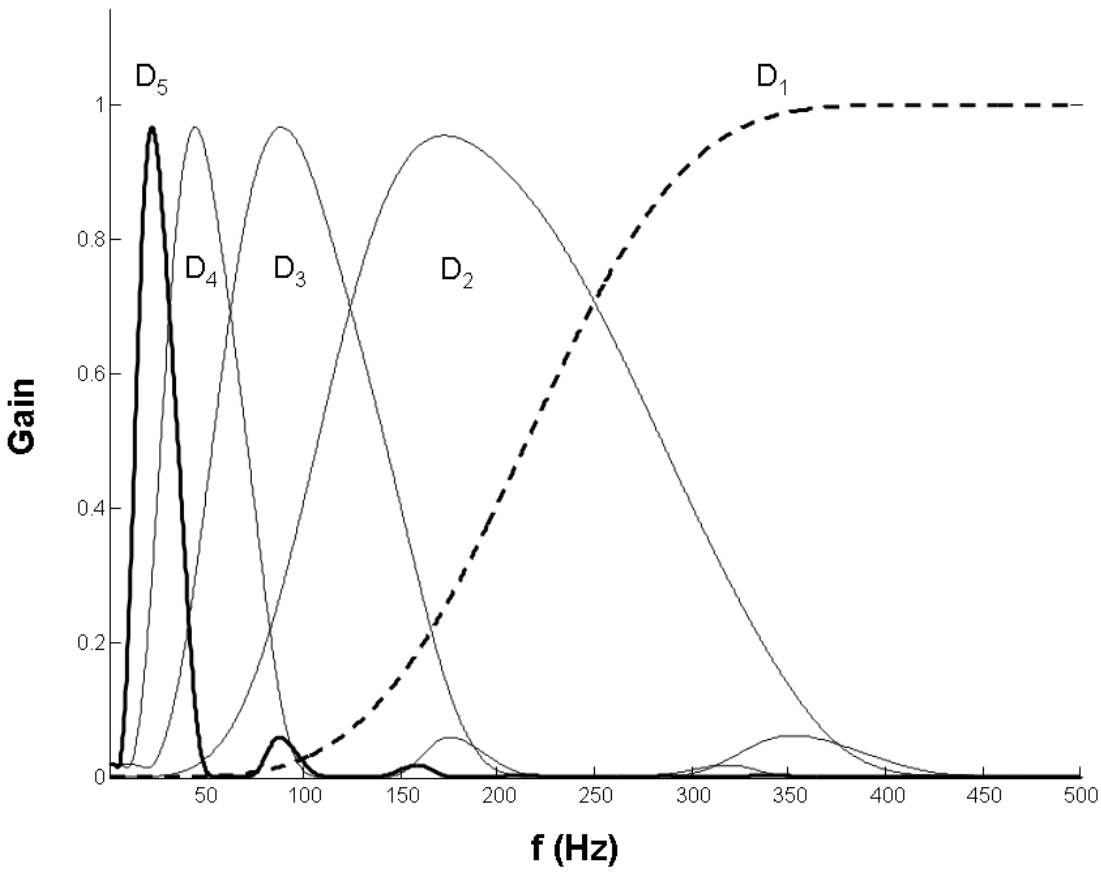

Fig 1. Frequency bands (calculated using the discrete Fourier transform) of the first five DWT details obtained using wavelet sym5. D5 (thick line) and D1 (thick dashed line) are the wavelet scales used to calculate WIRM1551, WIRM1M51, WIRE51 and WIRW51.

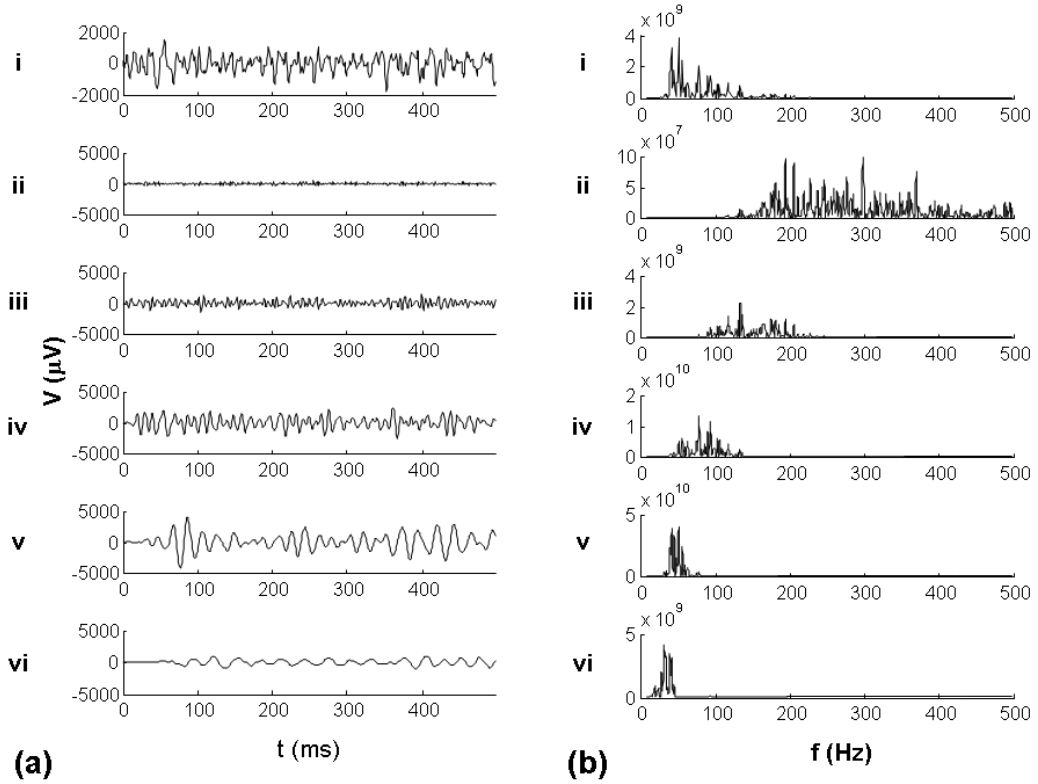

Fig 2. (a) sEMG original signal (i) and wavelet details at scales 1 to 5 (ii-iv). (b) Power spectrum using the discrete Fourier transform of the sEMG signal (i) and wavelet details at scales 1 to 5(ii-iv).

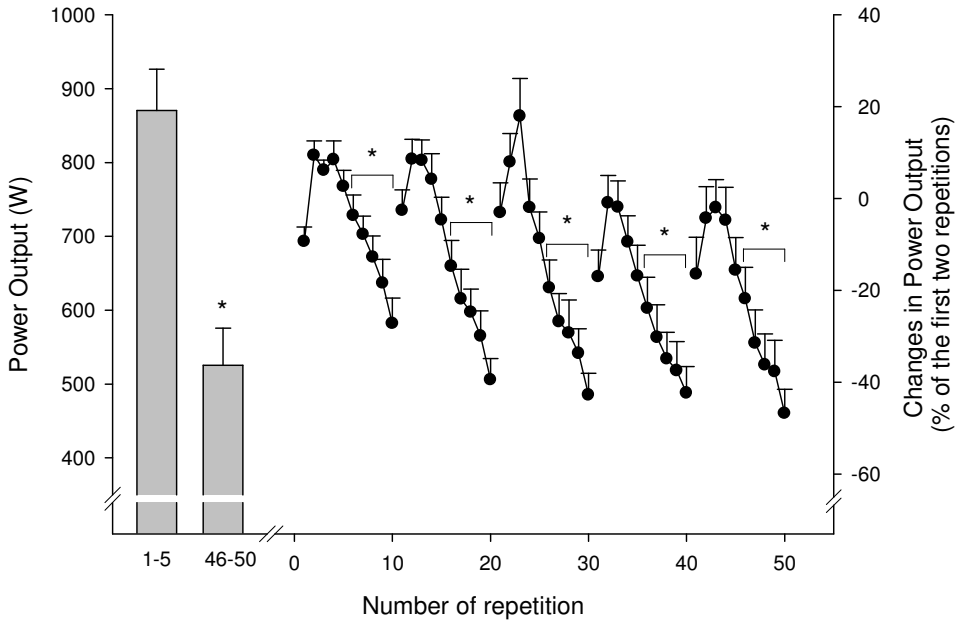

Fig 3. Percent changes in Muscle Power Output (mean ± standard error) during the 5 sets of 10 repetitions and mean of Muscle Power Output of the first and last five repetitions (mean ± standard error).

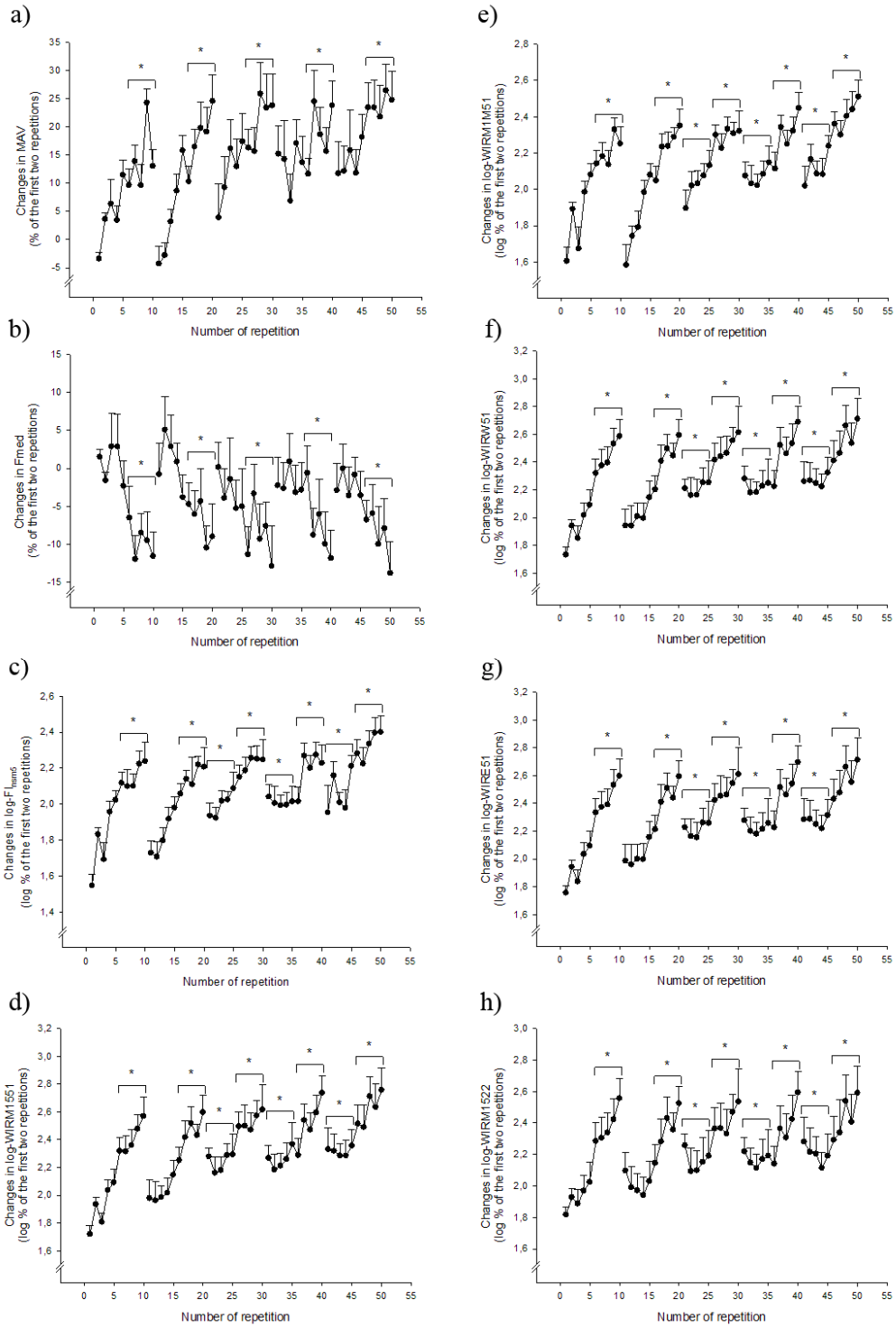

Fig 4. Percent changes in sEMG parameters (mean ± standard error) during the 5 sets of 10 repetitions. a) Mean Amplitude Voltage (MAV) b) Median frequency c) Logarithm of Dimitrov's index (FInsm5) d) Logarithm of WIRM1551 e) Logarithm of WIRM1551 f) Logarithm of WIRW51 g) Logarithm of WIRE51 h) Logarithm of WIRM1522.

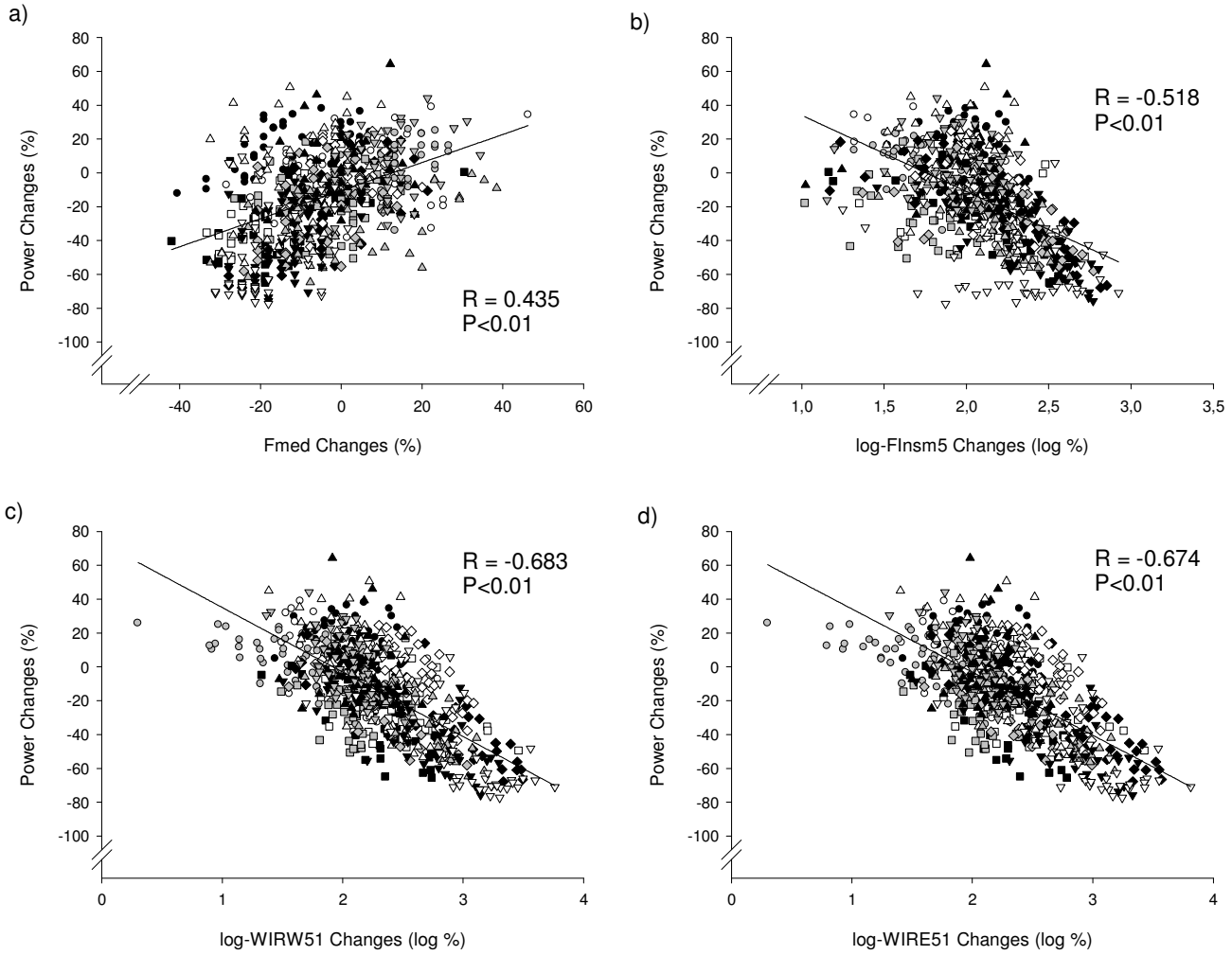

Fig 5. Regressions of Fmed (a), log-FInsm5 (b), log-WIRW51 (c) and log- WIRE51 (d) against muscle power output. The Pearson coefficients values are displayed.

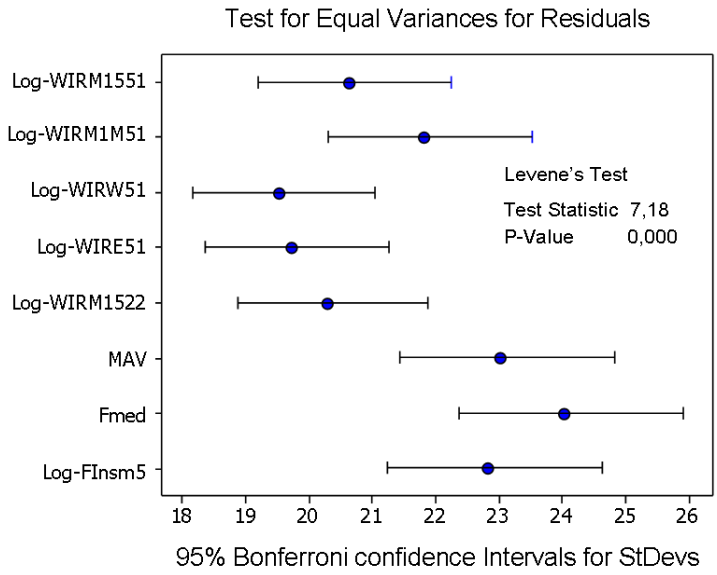

Fig 6. Levene's test. 95% Bonferroni confidence intervals for variances of the residuals of the regressions of the parameters.

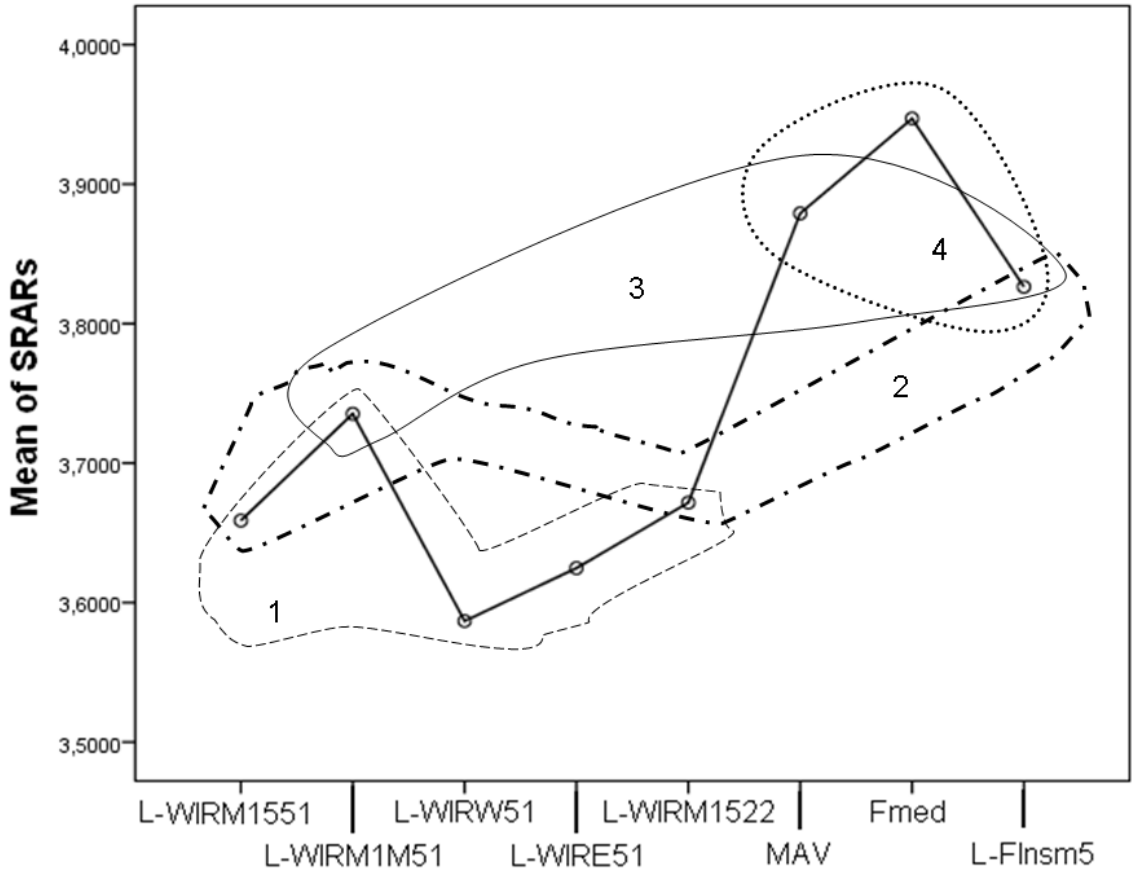

Fig 7. Mean of SRARs and homogeneous subgroups formed by Duncan's test.

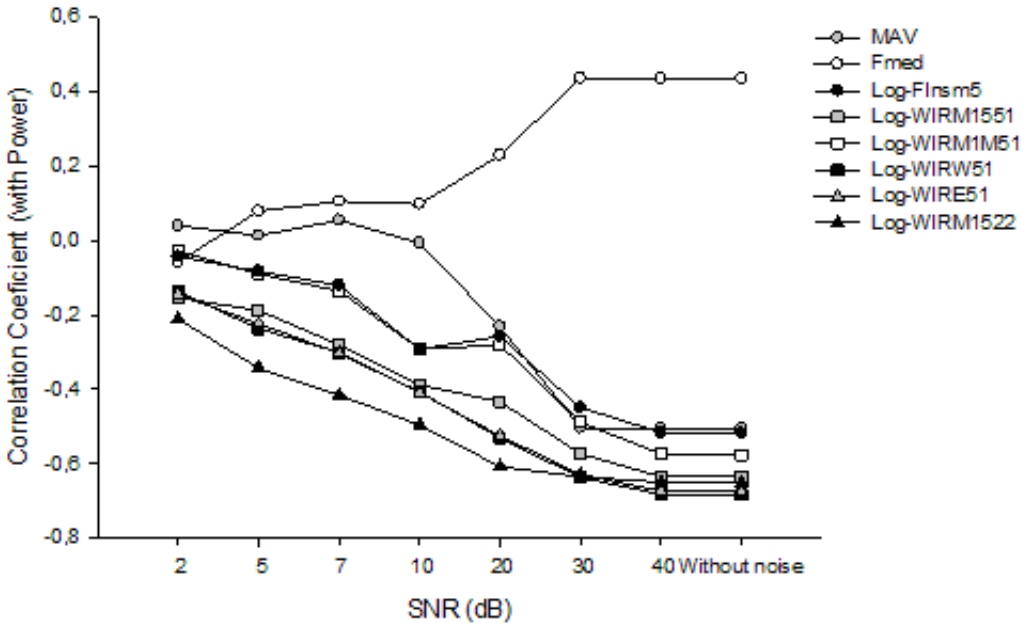

Fig 8. Correlation coefficient between sEMG parameters and muscle power output with different SNR value